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# A Multisensor-Multitarget Data Association Algorithm for Heterogeneous Sensors†

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## ABSTRACT

In this paper we present an algorithm to solve the static problem of associating data from three spatially distributed heterogeneous sensors, each with a set of detections at the same time. The sensors could be active (3D or 2D radars) or passive (EO sensors measuring the azimuth and elevation angles of the source). The source of a detection can be either a real target, in which case the measurement is the true observation variable of the target plus measurement noise, or a spurious one, i.e., a false alarm. In addition, the sensors may have nonunity detection probabilities. The problem is to associate the measurements from the sensors to identify the "real" targets, and to obtain their position estimates. Mathematically,this (static) measurement-target association problem leads to a generalized three-dimensional (3-D) matching problem, which is known to be NP-hard. In this paper, we present a fast, but near-optimal 3-D matching algorithm suited for estimating the positions of a large number of targets (>50) in a dense cluster for real-time applications. Performance results on several representative test cases solved by the algorithm are presented.

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## I. INTRODUCTION

The problem context for this paper is as follows: we are given a set of three *heterogeneous* sensors at different locations in a given surveillance area, each with a number of detections at a given time. With each detection, there is an associated measurement originating from a source. The set of sensors can consist of passive (Electro-Optical or ESM) and active (3D or 2D radar) sensors. A passive sensor measures the azimuth and elevation angles of the source, a 2D radar measures the range and azimuth angle of the source, while a 3D radar measures its complete position. Other configurations of sensors can also be used, e.g., with jammed radars. The source of detection can be either a real target, in which case the measurement is the true observation variable of the target plus some measurement noise, or a spurious one, i.e., a false alarm. We allow for missed detections by the individual sensors. In addition, each sensor has a *finite resolution*. Therefore, not all targets are detected by all sensors. The problem is to identify the number of targets present in the scenario, and find their (static) position estimates. The central problem of multisensor multitarget state estimation is that of data association - the problem of determining from which target, if any, a particular measurement originated. Measurements originating from a particular target can then be 3D-triangulated to estimate the states of the target. Typical applications are in sonar tracking and space surveillance using passive sensors and radar tracking in the presence of electronic countermeasure

For sparse scenarios, one may be able to place most targets into "unique" target planes defined by the sensors (EO or 3D radar) and a target. However, in scenarios involving a large number of targets in a dense cluster (for example a squadron of jets flying in formation), multiple targets may appear in a given plane resulting in the spurious (ghost) targets due to false triangulations of the line of sight measurements. The ghosting effect can be significantly reduced by using three sensors. A global optimization algorithm can then be employed to identify the most likely associations. Unfortunately, the 3-D [1] matching problem can be shown to be NP-hard[2] [2], even under the assumption of zero false alarm and unity detection probabilities.

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[1] For the matching problem, the number of dimensions is equal to the number of lists to be matched. Therefore, the dimension of the matching problem is the same as the number of sensors in the scenario. To avoid any confusion, the dimension of the matching algorithm is referred to as "3-D", and that of the measurement space as "3D".

[2] This means that an optimal algorithm for the multisensor (≥3) data association problem with a run-time bound that is a polynomial function of the number of sensor reports exists if and only if all the combinatorial problems belonging to class-NP, including the traveling salesman, maximum clique, and the satisfiability problems can be solved in polynomial time [1]. The evidence indicates that in all likelihood any problem which is NP-hard can not be solved by an algorithm of polynomial time complexity.



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In this paper we develop a three sensor data association algorithm suitable for dense clusters. The key features of the algorithm are as follows. First, we provide a unified framework to consider two-sensor and three-sensor detections. In dense clusters, sensor limitations may result in missed detections. Therefore, a certain number of targets are to be resolved using two-sensor measurements only. In our formulation, we assign *dimensionless* "costs" to two-sensor or three-sensor associations, thus enabling us to globally optimize the set of three-sensor and two-sensor detections. Second, we are not restricted to passive sensors only. In this paper, we present techniques to associate data from passive sensors, 3D and 2D radars. Our methodology extends naturally to any sensor type (Azimuth-only passive, jammed radars etc.). And third, we have developed a fast, iterative, near-optimal polynomial-time algorithm to globally optimize the association accuracy of measurements to targets detected by at least two sensors. The algorithm provides a conservative estimate of the proximity of a feasible solution to the optimal solution. Thus, in time-critical situations, we may truncate the algorithm at deadline, and still have a good feasible solution, and a measure of its accuracy. Solutions generated by the algorithm are typically within 2% of optimality. The details of the Lagrangian (dual) relaxation algorithm may be found in [3,4]. The Fortran Source Code of the algorithms presented in this paper are also available with the interactive software [5]. The performance results for some typical scenarios are presented in Section 3.

## II. PROBLEM FORMULATION

### 2.1. The Model

We assume that the position of target t is described by its Cartesian coordinates,

$$\underline{\omega}_t = [\, x_t \; y_t \; z_t \,]^T \qquad (2.1)$$

and that there are **T** targets in the surveillance region (**T** unknown and to be estimated by the algorithm). The three sensors are assumed to be non-collocated with known sensor positions

$$\underline{\omega}_s = [x_s \; y_s \; z_s]^T, \; s = 1,2,3 \qquad (2.2)$$

We allow missed detections and false alarms in our problem formulation. Each of the sensors can be one of the three types: a 3D radar, a 2D passive sensor or a 2D radar. The passive sensor measures the azimuth angle $\theta_{st}$ and elevation angle $\varphi_{st}$ of each potential target t. A 2D radar measures only the azimuth angle $\theta_{st}$ and the range $r_{st}$. A 3D radar measures all three, that is, the azimuth angle $\theta_{st}$, the elevation angle $\varphi_{st}$ and the range $r_{st}$. In order to present a unified sensor model, we define a (nonlinear) transformation $H_s$ on the true position vector $\underline{\omega}_t$ and sensor position $\underline{\omega}_s$ that generates the measurements. Let

$$\underline{m}_{st} = H_s(\underline{\omega}_t, \underline{\omega}_s) \tag{2.3}$$

where, $\underline{m}_{st} = [\theta_{st}, \varphi_{st}]$ for a passive sensor, $\underline{m}_{st} = [\theta_{st}, r_{st}]$ for a 2D radar and $\underline{m}_{st} = [\theta_{st}, \varphi_{st}, r_{st}]$ for a 3D radar.The measurement $i_s$ ( $i_s = 1,2,.., n_s$) of sensor s is modeled by:

$$\underline{z}_{si_s} = \begin{cases} \underline{m}_{st} + \underline{v}_{si_s} & \text{if origin is target } t \\ \underline{w}_{si_s} & \text{if spurious} \end{cases} \tag{2.4a}$$

and

$$\underline{z}_{si_s} = [\, z_{si_s}(1) \;\; z_{si_s}(2)] \tag{2.4b}$$

for passive sensor and 2D radars; and

$$\underline{z}_{si_s} = [\, z_{si_s}(1) \;\; z_{si_s}(2) \; z_{si_s}(3)\,] \tag{2.4c}$$

for 3D radars. The statistical errors associated with the measurements of true targets are assumed Gaussian

$$v_{si_s} \sim N(0, \Sigma_s) \tag{2.4d}$$

where $\Sigma_s$ is a diagonal matrix with the diagonal elements denoting the variance of the measurement errors.

The measurement noises are assumed to be independent across sensors. We let $P_{Ds}$ denote the detection probability of sensor s. We assume that the density of spurious measurements is given by

$$p_{\underline{w}_{si_s}}(\underline{w}) = \frac{1}{\Psi_s} \tag{2.4e}$$

where $\Psi_s$ is the field of view of sensor s. For example, $\Psi_s=\Psi_\theta\Psi_\phi\Psi_r$ if sensor s is a 3D radar; where $\Psi_\theta$ is the azimuth field of view, and $\Psi_\phi$ is the elevation field of view and $\Psi_r$ is the range field of view. The spurious measurements are independent of each other and of the target measurements.

To simplify the notation for incomplete measurement-target associations caused by missed detections, we add a dummy measurement $\underline{z}_{s0}$ to each of the measurements of sensor s. We denote the set of measurements from sensor s (including the dummy measurement $\underline{z}_{s0}$ ) by

$$\mathbf{Z}_s = \{\underline{z}_{si_s}\}_{i_s=0}^{n_s} \tag{2.5a}$$

and the set of measurements in the entire surveillance region by:

## 2.2. Partitioning of the Measurements

Consider a 3-tuple of measurements denoted by

$$Z_{i_1 i_2 i_3} = \{\underline{z}_{si_s}\}_{s=1}^{3} \tag{2.6}$$

The dummy measurements $\underline{z}_{s0}$ , s=1,2,3, enable us to consider all measurement-target associations (including single and two-sensor detections) as 3-tuples. The likelihood that sensor 1 missed the target at location $\underline{\omega}_t$ and that the measurements $i_2$ (>0) and $i_3$ (>0) of sensors 2 and 3 originated from the target t is given by :

$$\Lambda(Z_{0 i_2 i_3} | \underline{\omega}_t) = (1-P_{D_1})P_{D_2}P_{D_3}\,p(\underline{z}_{2i_2}|\underline{\omega}_t)p(\underline{z}_{3i_3}|\underline{\omega}_t) \tag{2.7}$$

In general, the likelihood function of the 3-tuple $Z_{i_1 i_2 i_3}$ being the set of measurements that originated from the same target at location $\underline{\omega}_t$ is the mixed probability density-probability function

$$\Lambda(Z_{i_1 i_2 i_3} | \underline{\omega}_t) = \prod_{s=1}^{3} [P_{Ds}p(\underline{z}_{si_s}|\underline{\omega}_t)]^{u(i_s)} \; [1-P_{Ds}]^{\{1-u(i_s)\}} \tag{2.8}$$

where u ( $i_s$ ) is the binary indicator function defined by

$$u(i_s) = \begin{cases} 0 & \text{if } i_s = 0 \text{ denoting a missed detection by sensor s} \\ 1 & \text{otherwise} \end{cases} \tag{2.9}$$

Denote by

$$\gamma = \{ Z_t ,\; Z_f \} \tag{2.10}$$

a feasible partition of the set Z into two subsets, namely, the subset of 3-tuples of measurements $Z_t$ = $\{ Z_{i_1 i_2 i_3} : i_s = 0,1,2,...,n_s ; s = 1,2,3\}$ associated with targets (tuples with at most one dummy measurement, i.e., 2 or 3 actual measurements), and the subset $Z_f = \{ z_{si_s} : i_s = 1,2,...,n_s ; s = 1,2,3 \} \equiv \{ Z_{i_1 00}, Z_{0 i_2 0}, Z_{00 i_3} : i_s = 1,2,...,n_s ; s = 1,2,3\}$, of spurious measurements not associated with any target (tuples with one actual measurement). Note that a partition also implies a set of true target positions (at the given time under consideration) to be estimated.The rationale for this division is that at least two measurements are needed for a full position estimate in the current static data association problem.

The feasibility of the partition requires the following :

(1) Each sensor measurement belongs to a target or a false alarm

$$\mathbf{Z} = Z_t \ \mathbf{U} \ Z_f \tag{2.11}$$

(2) Each sensor measurement belongs to one target only (Note that the dummy measurements may be associated with multiple targets. In other words, an unlimited number of dummy measurements, each associated with a unique target, may be added to the partition.)

$$Z_{i_1 i_2 i_3} \cap Z_{i'_1 i'_2 i'_3} = \varnothing \text{ for any } i_s \neq i'_s \ (i_s \neq 0, i'_s \neq 0), s=1,2,3 \tag{2.12}$$

Corresponding to a partition $\gamma$, one has the event

$$\zeta(\gamma) = \{ \text{ partition } \gamma \text{ is true } \} \tag{2.13}$$

We denote the set of all feasible partitions as

$$\Gamma = \{ \gamma \} \tag{2.14}$$

In order to normalize the likelihood function so that it is independent of the number of measurements from each sensor and of the number of hypothesized targets, we define the partition $\gamma_0 \in \Gamma$ as

$$\gamma_0 = \{ Z_t = \varnothing, Z_f = \mathbf{Z} \} \tag{2.15}$$

The partition $\gamma_0$ corresponds to the hypothesis that the number of targets $\mathbf{T}$ is zero, and that all measurements are spurious.

The most likely partition of the measurement set $\mathbf{Z}$ into target-originated measurements and false alarms is obtained by maximizing, over the set of all feasible partitions $\Gamma$, the ratio of the joint likelihood function of all the measurements in partition $\gamma$ to the likelihood function (LF) of all the measurements in partition $\gamma_0$. Note that this ratio is a dimensionless quantity. The maximization problem on the resulting *likelihood ratio* (LR) [3] is thus given by:

$$\max_{\gamma \in \Gamma} \frac{L(\gamma)}{L(\gamma_0)} \tag{2.16}$$

where

$$L(\gamma)=p[\mathbf{Z}|\zeta(\gamma)]=\Big[\prod_{Z_{i_1 i_2 i_3} \in \gamma} \Lambda(Z_{i_1 i_2 i_3}|\underline{\omega}_t)\Big] \cdot \Big[\prod_{s=1}^{3} \Big(\frac{1}{\Psi_s}\Big)^{n_s - T_s(\gamma)}\Big] \tag{2.17a}$$

and $T_s(\gamma)$ is the assumed number of targets in partition $\gamma$ that are detected by sensor s, and

$$L(\gamma_0) = p[\mathbf{Z}|\zeta(\gamma_0)] = \prod_{s=1}^{3} \Big(\frac{1}{\Psi_s}\Big)^{n_s} \tag{2.17b}$$

Since the true target positions $\underline{\omega}_t$ are unknown, we maximize the generalized likelihood ratio, wherein the true target positions $\underline{\omega}_t$ in Eqs. (2.8) and (2.17 a) are replaced by their maximum likelihood estimates $\hat{\underline{\omega}}_t$, obtained from the 3-tuple of measurements $Z_{i_1 i_2 i_3}$. That is,

$$\hat{\underline{\omega}}_t = \arg \max_{\underline{\omega}_t} \Lambda(Z_{i_1 i_2 i_3}|\underline{\omega}_t) \tag{2.18}$$

Therefore, Eq. (2.17 a) is replaced by

$$\hat{L}(\gamma)=p[\mathbf{Z}|\zeta(\gamma)] = \Big[\prod_{Z_{i_1 i_2 i_3} \in \gamma} \hat{\Lambda}(Z_{i_1 i_2 i_3}|\hat{\underline{\omega}}_t)\Big] \cdot \Big[\prod_{s=1}^{3} \Big(\frac{1}{\Psi_s}\Big)^{n_s - T_s(\gamma)}\Big] \tag{2.19}$$

[3] Since the LF, being a pdf, has a physical dimension, *one cannot compare*, for example, the LF of two targets with the LF of three targets. However, this comparison is possible using LR, since it is a dimensionless quantity [6].

where

$$\widehat{\Lambda}\,( Z_{i_1 i_2 i_3} \mid \underline{\widehat{\omega}}_t ) = \prod_{s=1}^{3} \left[ P_{Ds}\, N ( \underline{\widehat{\mu}}_{st} , \Sigma_s ) \right]^{u(i_s)} \cdot \left[ 1 - P_{Ds} \{ 1 - u(i_s) \} \right] \tag{2.20a}$$

and (using 2.3)

$$\underline{\widehat{\mu}}_{sL} = H_s ( \underline{\widehat{\omega}}_t, \underline{\omega}_s ) \tag{2.20b}$$

Note that, for a single sensor detection, $\widehat{\underline{\omega}}$ can not be estimated uniquely from Eq.(2.18) in the current static formulation. (However, when the static data association algorithm is used in a dynamic tracking application [7,8], these single measurements can be combined with existing tracks to update target position estimates.) To avoid targets with unobservable states, we make the assumption that *a target is detected by at least two sensors*. Thus, the 3-tuples of the form $Z_{i_1 00}$ (or $Z_{0 i_2 0}$ or $Z_{00 i_3}$) are uniquely associated with the subset $Z_f$ only, and, therefore represent spurious measurements in the current static formulation. In the dynamic tracking application, single sensor detections and spurious measurements are distinguished.

## 2.3 Measurement Partition as a 3-D Matching Problem

The maximization problem posed in Eqs. (2.16)-(2.20) is equivalent to the minimization of negative log-likelihood ratio given by :

$$J^* = \min_{\gamma \in \Gamma} J(\gamma) = \min_{\gamma \in \Gamma} \left[ \ln L(\gamma_0) - \ln \widehat{L}(\gamma) \right] \tag{2.21}$$

The contribution of elements of $Z_f$ to the negative log-likelihood ratio cancels out (see (2.17a), (2.17b)). Thus, Eq. (2.21) can be modified using Eqs. (2.17),(2.19) and (2.20) as:

$$J(\gamma) = \left[ \ln L(\gamma_0) - \ln \widehat{L}(\gamma) \right] = \sum_{Z_{i_1 i_2 i_3} \in Z_t} c_{i_1 i_2 i_3} \tag{2.22a}$$

where

$$c_{i_1 i_2 i_3} = \sum_{s=1}^{3} \Big\{ u(i_s) \Big[ -\ln(P_{D s}) + \frac{1}{2} ( \underline{z}_{s i_s} - \underline{\widehat{\mu}}_{s i_s} ) \Sigma_s^{-1} \cdot ( \underline{z}_{s i_s} - \underline{\widehat{\mu}}_{s i_s} )^T - \ln \frac{\Psi_s}{2\pi \mid \Sigma_s \mid^{1/2}} \Big] - [1 - u(i_s)] \ln(1 - P_{Ds}) \Big\} \tag{2.22b}$$

The minimization of the negative log-likelihood ratio can be recast as a 3-D matching problem as follows. Define the binary event variables :

$$\rho_{i_1 i_2 i_3} = \begin{cases} 1 & \text{if the 3-tuple } Z_{i_1 i_2 i_3} \in \gamma \\ 0 & \text{otherwise} \end{cases} ; \; i_s = 0,1,2,\ldots n_s ; s=1,2,3 \qquad (2.23)$$

where associations of the form $\{\rho_{i_1 00}, \rho_{0 i_2 0}$ or $\rho_{00 i_3}\}$ denote spurious measurements. Since the addition of measurement $z_{1 i_1} \equiv Z_{i_1 00}$ to subset $Z_f$ has no cost penalty, we set $c_{i_1 00} = c_{0 i_2 0} = c_{00 i_3} = 0$. Note that the sum of squares of the differences between the measurements $\underline{z}_{s i_s}$ and their estimates $\underline{\mu}_{s i_s}$ in Eq. (2.22) is the goodness of fit of a triplet. Since there exists a one-to-one mapping between the binary events $\rho_{i_1 i_2 i_3}$ and the feasible partition $\gamma$, the minimization of the negative log-likelihood ratio can be recast as the following 3-D matching problem:

$$J^* = \min_{\rho_{i_1 i_2 i_3} \in P} J(\rho) \qquad (2.24a)$$

where

$$J(\rho) = \sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} c_{i_1 i_2 i_3} \rho_{i_1 i_2 i_3} \qquad (2.24b)$$

The constraint set P, denoting the set of all feasible partitions, is formulated as the set of linear equalities:

$$\sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \rho_{i_1 i_2 i_3} = 1 \quad \text{for all } i_3 = 1,2,\ldots, n_3 \qquad (2.25a)$$

$$\sum_{i_3=0}^{n_3} \sum_{i_1=0}^{n_1} \rho_{i_1 i_2 i_3} = 1 \quad \text{for all } i_2 = 1,2,\ldots, n_2 \qquad (2.25b)$$

$$\sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} \rho_{i_1 i_2 i_3} = 1 \quad \text{for all } i_1 = 1,2,\ldots, n_1 \qquad (2.25c)$$

The optimization problem formulated in Eqs. (2.24)-(2.25) is a generalized 3-D matching problem presented later in Section 3.

## 2.4 Preprocessing in the 3-D Matching Problem (Fine Gating)

Consider three measurements, $z_{1i_1}$, $z_{2i_2}$ and $z_{3i_3}$ (with at most one dummy) from sensors 1,2 and 3 respectively. The corresponding 3-tuple $Z_{i_1 i_2 i_3}$ may be considered a candidate measurement-target association if and only if $c_{i_1 i_2 i_3} < 0$. This is because, if $c_{i_1 i_2 i_3} > 0$, the addition of $Z_{i_1 i_2 i_3}$ to the subset $Z_t$ of measurement-target associations will actually *increase* the cost $J(\rho)$ in Eq. (2.21), whereas adding $\{z_{1i_1}, z_{2i_2}, z_{3i_3}\}$ to the subset $Z_f$ of spurious measurement has no cost penalty. Therefore, all 3-tuples $Z_{i_1 i_2 i_3}$ with $c_{i_1 i_2 i_3} > 0$ can be *eliminated* from the list of candidate associations by setting the corresponding binary event variables $\rho_{i_1 i_2 i_3} = 0$. This is referred to as the"fine gating scheme" in Section 3.

# III. APPLICATION RESULTS

## 3.1 Scenario Description

If the scenario is reasonably sparse and/or the sensors are very accurate, one may be able to place each target in a unique plane, and eliminate the problem of ghosting. A relatively simple sorting algorithm can then pick the feasible solution. However, due to measurement inaccuracies and nonuniform target distribution, multiple targets may lie in a plane. In addition, due to the finite resolution of sensors, some targets are unresolved at some sensors. The scenario can be further complicated by heavy clutter, and missed detections. In many cases, the false alarm probabilities are unknown or time-varying. In this section, we evaluate the performance of our data association algorithm under such adverse conditions.

The elevation fields of view of all three sensors[4] are (28°, 33°). Sensors 1 and 3 are 2D passive senors measuring azimuth and elevation angles of targets. The azimuth field of view of sensor 1, positioned at (-1000,250,0), is ( 58.2°, 63.2° ) and that of sensor 3, positioned at (1000,250,0), is (116.8°, 121.8° ). Sensor 2 is positioned at (0,0,0) and has a head-on view of the target cluster. Its azimuth field of view is (87.5°, 92.5°). We simulate 3 different sensor configurations observing the same scenario. In configuration 1, we use three 2D passive sensors. In configuration 2, sensor 2 is a 2D radar measuring azimuth and range only. In configuration 3, sensor 2 is a 3D radar measuring azimuth, elevation and range. For configurations 2 and 3, the range field of view of sensor 2 is (2275, 2425) distance units.

[4] We use the convention that East is 0° azimuth and horizontal is 0° elevation.The reference point for our coordinate system is sensor 2 located at (0,0,0). Each Cartesian unit distance is equivalent to 1000 meters.

We simulated 64 targets in a cluster. They were arranged in four vertical planes corresponding to y = 2075; y = 2050; y = 2025 and y = 2000, respectively. Each plane consisted of 16 targets. The typical inter-target spacings are about 20 units in x and z directions for the y=2075 plane; this spacing is progressively increased for the planes nearer to the sensors. The scenario thus simulates 64 targets in 4 wavefronts fanning out slightly as they approach the coordinates (0,0,0). In addition, for each simulation run, we randomly perturb the target positions around its typical position. Therefore, the actual position of a target position for a particular run is given by (x + u, y + v, z + w), where (x,y,z) is the typical target position, and u,v,w are uniform random variables in the range [+5,-5].

Finite resolution of the sensors is explicitly modelled. Results are presented for three different sensor resolution capabilities. For passive sensors and 3D Radars, the image area is assumed to consist of 500x500 azimuth-elevation cells in case 1; 1000x1000 cells in case 2 and 2000x2000 cells in case 3. For 2D Radars, 500, 1000 & 2000 azimuth cells are assumed. The standard deviation of the measurement noise is assumed to be 1/5 of a resolution cell. Recall that the field of view of each sensor is $5^o$ in both azimuth and elevation. Therefore, $\sigma_\theta = \sigma_\phi = 0.002^o$ in case 1, $\sigma_\theta = \sigma_\phi = 0.001^o$ in case 2, and $\sigma_\theta = \sigma_\phi = 0.0005^o$ in case 3. For 2D and 3D Radars, three different range measurement accuracies, $\sigma_r = 0.05$, 0.02 and 0.01 (corresponding to 50 meters, 20 meters, and 10 meters, respectively), were simulated. For a passive sensor, if two targets are close enough so that both their azimuth and elevation measurements are separated by less than 5 standard deviations, a single detection with an averaged measurement is reported. For a 3D radar, two targets are unresolved and reported as a single detection, if azimuth , elevation and ranges of the two targets are separated by less than 5 standard deviations. Similarly, for a 2D radar, either or both the azimuth and range measurements of any pair of targets should be sufficiently separated to be able to resolve the two targets.

The detection probability of each sensor was assumed to be 0.95. The false alarm rate was fixed at $10^{-5}$ per resolution cell for passive sensors and 2D radars, and $10^{-8}$ per resolution cell for the 3D radars. This resulted in rather heavy clutter for sensors in some cases. For example, for a passive sensor with 2000x2000 azimuth-elevation cells, the number of false alarms per sensor report is a Poisson random variable with mean = $10^{-5}$x2000x2000 = 40, which is comparable to the number of targets present in the scenario! Nevertheless, this heavy clutter constitutes a hypothetical, yet possible, surveillance scenario.

## 3.2 Results for Different Sensor Configurations

Table I presents simulation results for the 3 passive sensor case. On the average, 63 targets are detected by 2 or more sensors, 52 of which are detected by all three sensors. The results demonstrate a uniform association accuracy of 95%, in spite of the heavy clutter (an average of 38 false alarm reports from each sensor) in case 3.

In many surveillance scenarios, accurate 3D radars are also available. For this simulation, Sensor 2 was replaced by a 3D Radar. The 3D radar measures full target positions. This information appeared to aid the gating scheme, resulting in a sparse assignment graph and approximately 25% reduction in the CPU time over the 3 passive sensor case. Moreover, the association accuracy and position estimates are also marginally improved, as shown in Table II. Table III presents the results for different range measurement accuracies of the 3D Radar. An improvement of range accuracy has little effect on the association accuracy for this particular scenario.

| | **Case 1** 500 cells | **Case 2** 1000 cells | **Case 3** 2000 cells |
|---|---|---|---|
| Total Number of False Alarms in scenario | 9.21 | 31.5 | 114 |
| Targets detected by 2 or more sensors | 63.13 | 63.02 | 62.74 |
| Targets detected by only 2 sensors | 11.58 | 11.63 | 11.77 |
| Number after Coarse Gating | 240.39 | 220.8 | 214.8 |
| Number after Fine Gating | 240.35 | 220.8 | 214.8 |
| Average CPU Time (seconds; 25MHz-386i) | 19.5 | 19 | 19.3 |
| Number of Identified Targets | 68.08 | 67.58 | 69.26 |
| Percent Correct Association | 94.8 | 95.13 | 94.95 |
| Average Error in Position Estimate | 0.147 | 0.074 | 0.037 |

TABLE I : Results of 100 Monte-Carlo runs for the 64 target scenario. (Sensor configuration 1 - three passive sensors)

Finally in Tables IV and V we present the results for sensor configuration 3, in which sensor number 2 is replaced by a 2D Radar. Since the 2D sensors do not measure elevation angles of the target, gating using hinge angles is not possible. This results in inefficient gating and causes CPU times as high as 10 times the 3 passive sensor case. However, the association accuracy is approximately the same as that of the 3 passive senor case.

| | **Case 1** 500 cells | **Case 2** 1000 cells | **Case 3** 2000 cells |
|---|---|---|---|
| Total Number of False Alarms in scenario | 11.75 | 29.24 | 97.3 |
| Targets detected by 2 or more sensors | 63.2 | 63.42 | 63.3 |
| Targets detected by only 2 sensors | 12.45 | 10.38 | 10.86 |
| Number after Coarse Gating | 239.61 | 224.68 | 215.84 |
| Number after Fine Gating | 208.54 | 206.99 | 202.6 |
| Average CPU Time (seconds; 25MHz-386i) | 15.88 | 16.44 | 16.02 |
| Number of Identified Targets | 63.87 | 64.06 | 65.18 |
| Percent Correct Association | 96.31 | 96.94 | 96.94 |
| Average Error in Position Estimate | 0.085 | 0.052 | 0.031 |

TABLE II : Results of 100 Monte-Carlo runs for the 64 target scenario. (Sensor configuration 2 - two passive and one 3D radar)

| 500 resolution cells | $\sigma_r$ = 50 m. | $\sigma_r$ = 20 m. | $\sigma_r$ = 10 m. |
|---|---|---|---|
| Total Number of False Alarms in scenario | 11.75 | 13.31 | 15.6 |
| Targets detected by 2 or more sensors | 63.2 | 63.22 | 63.2 |
| Targets detected by only 2 sensors | 12.45 | 12.2 | 12.3 |
| Number after Coarse Gating | 239.61 | 244.27 | 235.09 |
| Number after Fine Gating | 208.54 | 213.05 | 205.28 |
| Average CPU Time (seconds; 25MHz-386i) | 15.88 | 16.56 | 17.02 |
| Number of Identified Targets | 63.87 | 63.96 | 63.61 |
| Percent Correct Association | 96.31 | 96.6 | 96.25 |
| Average Error in Position Estimate | 0.085 | 0.075 | 0.072 |

TABLE III : Results of 100 Monte-Carlo runs for the 64 target scenario. (Sensor configuration 2 - two passive and one 3D radar)

| | **Case 1** 500 cells | **Case 2** 1000 cells | **Case 3** 2000 cells |
|---|---|---|---|
| Total Number of False Alarms in scenario | 9.4 | 29.8 | 86.7 |
| Targets detected by 2 or more sensors | 63 | 62.9 | 63.1 |
| Targets detected by only 2 sensors | 11.4 | 11.6 | 10.7 |
| Number after Coarse Gating | 955.4 | 1011.2 | 1007.4 |
| Number after Fine Gating | 304 | 254.9 | 257.8 |
| Average CPU Time (seconds; 25MHz-386i) | 154 | 157.2 | 171.1 |
| Number of Identified Targets | 70.4 | 69.9 | 71.4 |
| Percent Correct Association | 94.6 | 94.9 | 95.1 |
| Average Error in Position Estimate | 0.101 | 0.058 | 0.035 |

TABLE IV : Results of 100 Monte-Carlo runs for the 64 target scenario. (Sensor configuration 3 - two passive and one 2D radar)

| 500 resolution cells | $\sigma_r$ = 50 m. | $\sigma_r$ = 20 m. | $\sigma_r$ = 10 m. |
|---|---|---|---|
| Total Number of False Alarms in scenario | 9.4 | 13.9 | 21.9 |
| Targets detected by 2 or more sensors | 63 | 63.1 | 63.1 |
| Targets detected by only 2 sensors | 11.4 | 11.4 | 11.4 |
| Number after Coarse Gating | 955.4 | 1022.7 | 1059.17 |
| Number after Fine Gating | 304 | 298.5 | 296.5 |
| Average CPU Time (seconds; 25MHz-386i) | 154 | 165.1 | 166.7 |
| Number of Identified Targets | 70.4 | 72.6 | 73.4 |
| Percent Correct Association | 94.6 | 94.5 | 94.5 |
| Average Error in Position Estimate | 0.101 | 0.092 | 0.092 |

TABLE V : Results of 100 Monte-Carlo runs for the 64 target scenario. (Sensor configuration 3 - two passive and one 2D radar)

## 3.3 Discussion of Results in Tables I-V

The association accuracy of the algorithm was about 95% for all the sensor configurations used. In fact, the association accuracy appears to be independent of the sensor type and resolution capabilities. The 5% missassocication was due to the poor target geometry. Although the field of view of each sensor was $5^o$ in azimuth and elevation, all the targets were located in a cluster spanning less than $2^o$ in azimuth and elevation. The targets were arranged in four closely spaced vertical planes. In each vertical plane, the targets were placed in a regular rectangular grid.This causes some ghosting and resolution problems. For each run, the target positions were perturbed by $\pm 5$ units in each direction. A significant number of targets (about 16 in the 500 cell resolution case in Table I) could not be placed on unique planes and an average of three targets were unresolved per sensor list due to random alignment of targets in the back plane behind those in the front plane. In higher resolution cases, the false alarm rates were significantly higher. Therefore, the advantage gained, if any, by higher sensor accuracy, was mitigated by the large number false alarms.

The average number of targets detected by all three sensors is approximately 52, about 11 other targets are detected by only two sensors as a result of non-unity sensor detection probability and finite resolutions of sensors. For the 500 resolution cell case in Table I, for example, an average of 2.5 targets per list were unresolved, and another 3.2 missed due to nonunity sensor detection probability. The data association algorithm, however, consistently identified an average of 60 of the 63 targets detected by two or more sensors, thus illustrating the capability of the algorithm to integrate two-sensor and three-sensor detections. The algorithm is also remarkably robust to heavy clutter. Even with 38 false alarms per list, which translates to 6 false reports for every 10 targets, the algorithm exhibits negligible degradation in association accuracy.

The average CPU time required by the 3-D Matching algorithm on a SUN386i computer is approximately 3 seconds. The average CPU time required by the entire data association algorithm for sensor configurations 1 and 2 (Tables I-III) was between 15 and 20 seconds. Therefore, a major part of the time (upto 80%) is spent in the cost assignment phase (non-linear Least Squares). The coarse gating scheme based on hinge angles is both cheap and efficient. However, the final cost assignment phase includes the formation of nonlinear least squares estimates of true target positions from measurements in the candidate association - which typically take about 0.05 seconds per candidate association. An increased number of candidate associations would therefore result in unacceptably long computation times. Note that for denser clusters, involving multiple targets in the same ghosting plane, the number of candidate associations could increase dramatically.

The 2D radars do not measure the elevation of the targets. It is, therefore, not possible to form hinge angles for detections by the 2D radar. This results in inferior coarse gating and a large number of candidate associations. It also causes an increased number of "ghost" associations, as is evident from the increased number of "identified targets" in tables IV and V.

Note that the cost computation phase is highly parallelizable, Therefore, in time critical applications, costs of candidate associations can be computed independently of each other on multiple processors, resulting in a linear speedup with increasing numbers of processors.

## IV. CONCLUSIONS

Any large-scale surveillance and/or defense system is intrinsically a multisensor-multitarget system, e.g., air-traffic control systems, a navigation and guidance system or the Space Surveillance and Tracking System (SSTS). Many of these systems employ a wide variety of sensors ( Radar, IR detector, sonar etc.). In this paper, we presented an algorithm to integrate reports from multiple heterogeneous sensors to estimate target positions in a dense target environment.

The data association algorithm presented here has robust performance in the presence of very heavy clutter. It deals with two sensor and three sensor detections in an unified framework. Even though we intentionally simulated a reasonably difficult sensor- target geometry, the data association algorithm produced consistently good association accuracy (~ 95%), even though about 17% of the targets are detected by only 2 sensors. Furthermore, *close to half* the detections at each sensor were *false* and in spite of this, the overall performance is remarkably good - only 10% extra (*false* ) targets were accepted by the data association algorithm.

In this paper we simulated various sensor configurations. The three passive sensor configuration performs satisfactorily, although, replacing one of the passive sensors with a 3D radar increases the association accuracy by about 1%. A 3D radar also reduces the number of candidate associations and hence the time required to assign costs to the associations. Moreover, the graph for the 3-D matching problem is sparser compared to the three passive sensor case, which also speeds up the matching algorithm. The overall savings in CPU time is about 25% compared to that of a three passive sensor case. The 2D radar does not measure the elevation of the source of detection; hence, hinge angle gating is not possible for associations involving measurements from 2D radar. This result in an increase in the number of candidate associations and upto 10 fold increase in CPU time compared to the three passive sensor case. The data association algorithm could benefit from a computationaly cheap, yet efficient, gating scheme for 2D radars.

The challenge in tracking problems is not only to estimate positions, but also to form tracks and estimate the velocity and acceleration of each target. The data association problem can be reformulated to associate data from multiple scans from multiple sensors, and to form estimates of target states. The optimization problem can then be solved using a multi-dimensional matching problem as outlined in [12] . Moreover, we may virtually eliminate the ghosting problem in target position estimation by associating angle only measurements of four or more passive sensors. The *price* update in [9,10] extends naturally to M-dimensional ( $M \geq 3$) matching algorithms. These issues are currently under investigation.

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